

Variability in surface BRDF at different spatial scales (30 m–500 m) over a mixed agricultural landscape as retrieved from airborne and satellite spectral measurements

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Abstract – Over the past decade, the role of multiangle remote sensing has been central to the development of algorithms for the retrieval of global land surface properties including models of the bidirectional reflectance distribution function (BRDF), albedo, land cover/dynamics, burned area extent, as well as other key surface biophysical quantities represented by the anisotropic reflectance characteristics of vegetation. In this study, a new retrieval strategy for fine-to-moderate resolution multiangle observations was developed, based on the operational sequence used to retrieve the Moderate Resolution Imaging Spectroradiometer (MODIS) Collection 5 reflectance and BRDF/albedo products. The algorithm makes use of a semiempirical kernel-driven bidirectional reflectance model to provide estimates of intrinsic albedo (i.e., directional-hemispherical reflectance and bihemispherical reflectance), model parameters describing the BRDF, and extensive quality assurance information. The new retrieval strategy was applied to NASA’s Cloud Absorption Radiometer (CAR) data acquired during the 2007 Cloud and Land Surface Interaction Campaign (CLASIC) over the well-instrumented Atmospheric Radiation Measurement Program (ARM) Southern Great Plains (SGP) Cloud and Radiation Testbed (CART) site in Oklahoma, USA. For the case analyzed, we obtained ~1.6 million individual surface bidirectional reflectance factor (BRF) retrievals, from nadir to 75° off-nadir, and at spatial resolutions ranging from 3 m – 500 m. This unique dataset was used to examine the interaction of the spatial and angular characteristics of a mixed agricultural landscape; and provided the basis for detailed assessments of: (1) the use of a priori knowledge in kernel-driven BRDF model inversions; (2) the interaction between surface reflectance anisotropy and instrument spatial resolution; and (3) the uncertainties that arise when sub-pixel differences in the BRDF are aggregated to a moderate resolution satellite pixel. Results offer empirical evidence concerning the influence of scale and spatial heterogeneity in kernel-driven BRDF models; providing potential new insights into the behavior

and characteristics of different surface radiative properties related to land/use cover change and vegetation structure.

Keywords: BRDF; Surface albedo; Cloud Absorption Radiometer; MODIS; CLASIC'07; ARM Climate Research Facility; US Southern Great Plains; linear model; inversion; a priori knowledge; 6S; AERONET; spatial analysis; APU; airborne measurements; multiangle remote sensing; EOS land validation core sites.

1. Introduction

Techniques for determining the structure and optical properties of complex heterogeneous environments using multiangle remote sensing are crucial for understanding the effects of environmental change on vegetation structure and thus improve our ability to model terrestrial carbon cycle dynamics and to characterize the ecological functioning of many ecosystems. Recent studies have made considerable progress in developing algorithms for the extraction of quantitative information on terrestrial surface heterogeneity at the subpixel scale (Sandmeier et al. 1998; Widlowski et al. 2001; Pinty et al. 2002; Armston et al. 2007; Chopping et al. 2008; Hill et al. 2008). In general, this has been achieved by examining how different manifestations of the surface reflectance anisotropy over the angular range (e.g., bowl-shape vs. bell-shape anisotropy features) are directly related to canopy physiognomy and structure (e.g. canopy height, size, inter-distance between trees, and background vs. foliage contributions).

In the past, previous experiments have generally followed the central assumption that “the potential to detect structural heterogeneity is independent of the spatial scale corresponding to the pixel size” (Pinty et al. 2002). In line with this assumption, earlier studies have treated satellite BRDF/albedo retrievals as being observed over a homogeneous landscape; thus allowing direct “point-to-pixel” comparisons (Hautecoeur and Leroy 1998; Liang et al. 2002; Jin et al. 2003a; Jin et al. 2003b; Salomon et al. 2006; Chen et al. 2008; Knobelspiesse et al. 2008; Liu et al. 2009; Rutan et al. 2009). Recent studies have further evaluated surface albedo retrievals both in terms of the spatial correspondence (or representativeness) of the field (or tower-based) data and its relationship to the larger satellite pixel (Susaki et al. 2007; Román et al. 2009; Román et al. 2010). However, because of the impact of view and solar zenith angle (SZA) dependencies, sub-grid scale spatial heterogeneity, and other underlying sources of variation that introduce

measurement uncertainties within the ground resolution element (GRE) of satellite retrievals; the BRDF (and thus albedo) of certain ecosystems can only be correctly sampled with airborne multiangle measurements (Walthall et al. 2000). Among key biomes affected by these sources of error are mixed-forest canopies (Johnson 1994; Russell et al. 1997b), tropical savannas (Hill et al. 2008; Georgiev et al. 2009), shrublands (Chopping et al. 2004), as well as snow-covered environments (Lyapustin et al. 2009). Furthermore, recent studies contend that subpixel vegetation structure is only detectable when obtaining measurements near the principal plane; i.e., where BRDF effects are most pronounced (Chen et al. 2005). Consequently, the exact nature of these angular-to-structural relationships has been difficult to quantify at the relevant view-angle geometries of satellite sensors that routinely sample the BRDF over a single overpass (Leroy et al. 1997; Diner et al. 1998b) or in the course of multiple overpasses (Schaaf et al. 2002; Muller et al. 2007).

Because of the difficulties of estimating, validating, and conveying measurement differences between sensors and in-situ measurements, there is a need to directly examine the accuracy, precision, and uncertainty (APU) of land surface BRDF products; particularly, across complex heterogeneous environments. Accordingly, this study presents a new BRDF/albedo retrieval scheme that uses high quality, multiresolution, and multispectral surface bidirectional reflectance factor (BRF) measurements acquired by NASA's Cloud Absorption Radiometer (CAR) (King et al. 1986; Gatebe et al. 2003). The retrieval strategy, described in Section 2, is based on the operational Moderate Resolution Imaging Spectroradiometer (MODIS) algorithm for retrieving Surface Reflectance (Vermote et al. 1997; Kotchenova et al. 2006), BRDF and albedo (Schaaf et al. 2002; Schaaf et al. 2011), and was used to examine the two major assumptions underlying semi-empirical kernel-driven BRDF models (Roujean et al. 1992; Lewis 1995; Wanner et al. 1995)

using data acquired over the well-instrumented Atmospheric Radiation Measurement Program (ARM) Southern Great Plains (SGP) Cloud and Radiation Testbed (CART). The first assumption contends that “linear BRDF models can implicitly model surface heterogeneities.” The second one argues that “spatial degradation of modeled bidirectional reflectance can be achieved through degradation of the model parameters describing the BRDF.” The first assumption was tested by computing the model-fits error (RMSE) of surface BRDF retrievals acquired directly from CAR data, and then establishing the departure of RMSE values obtained from BRDF retrievals that employ an ancillary database of a priori archetypal BRDF shapes (*cf.*, Section 4.1). To test the second assumption, the interaction between instrument spatial resolution and surface reflectance anisotropy was examined by assessing the distribution of relative differences in surface BRF retrievals obtained from CAR and MODIS BRDF model inversions at different spatial scales and across different spectral regions and view-angle geometries (*cf.*, Section 4.2).

2. BRDF/albedo retrieval scheme

The new scheme has three main functional components: atmospheric correction (Fig. 1a), geolocation and gridding (Fig. 1b), and BRDF inversion (Fig. 1c). The aim of atmospheric correction is to retrieve surface-level bidirectional reflectance factor (BRF) measurements from remotely sensed CAR data, which is contaminated by the effects of atmospheric particles and gases through absorption and scattering of the radiation, especially from the Earth’s surface. The aim of geolocation and gridding is to determine the center coordinates of each observation along the instrument scan line (since the CAR data provide only the geolocation of the nadir-looking ground resolution element of each scan), and to register the data to a common grid to maintain consistency across datasets. The aim of BRDF inversion is to fit atmospherically-corrected BRFs

to retrieve the RossThick-LiSparseReciprocal (RTLSR) model parameters describing the BRDF in each CAR grid cell and spectral band. The retrieval scheme also performs angular integrations to derive intrinsic land surface albedos for each spectral band, and is supported by extensive quality assurance (QA) information.

2.1. Atmospheric correction

In the past, various radiative transfer schemes have been used for the atmospheric correction of CAR data (*cf.*, Gatebe et al., 2003; 2005; Lyapustin et al. 2009). In this study, we used the second simulation of satellite signal in the solar spectrum (6S) model, version 6SV1.1 (Vermote et al. 1997; Kotchenova et al. 2006), which is the heritage model used in the operational MODIS algorithm for retrieving Surface Reflectance. The 6S code is a radiative transfer model based on the successive orders of scattering method. The spectral resolution of the model is 2.5 nm, and the aerosol layer is divided into 13 layers with a scale height of 2 km. The model assumes the atmosphere consists of fixed gases: O₂, O₃, H₂O, CO₂, CH₄, and N₂O. The concentration of O₂, CO₂, CH₄, and N₂O are assumed to be constant and uniformly mixed in the atmosphere. The 6S model allows us to determine the attenuation of solar irradiance under cloudless conditions at the surface. It removes the effects of Rayleigh scattering, aerosol attenuation, and ozone and water vapor absorption, provided we know the key characteristics of the atmosphere, such as the atmospheric optical thickness, aerosol model, and absorbing gas concentration. Since the CAR measurements were acquired during intensive field campaigns, coincident and co-located ground-based and airborne data needed as input to the 6S model exist. For example, aerosol parameters can be obtained from ground-based sunphotometer measurements (Holben et al. 1998), or from the Ames Airborne Tracking Sunphotometer (Russell et al. 1999), or retrieved from CAR

139 measurements (Fig. 1a) (Gatebe et al. 2010).

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141 2.2. Geolocation and gridding

142 Since the CAR has a wide swath (190°) and an instantaneous field of view (IFOV) of 1°,
 143 there is a need to determine the center coordinates of each observation ($lat_{off-nadir}$, $lon_{off-nadir}$)
 144 along the scan line from nadir to near-horizon (i.e., $0^\circ \leq \theta_v \leq 75^\circ$). We used the expression,

$$145 \quad lat_{off-nadir} = \sin^{-1} \left[\sin(lat_{nadir}) \cdot \cos \left[\frac{d}{R_\otimes} \right] + \cos(lat_{nadir}) \cdot \sin \left[\frac{d}{R_\otimes} \right] \cdot \cos(\phi_v) \right] \quad (1)$$

$$146 \quad lon_{off-nadir} = - \left(a - 360 \cdot \left\lfloor \frac{a}{360^\circ} \right\rfloor \right) + 180 \quad (2)$$

147 where:

$$148 \quad d = h \tan(\theta_v) \quad (3)$$

$$149 \quad a = lon_{nadir} - dlon + 180^\circ \quad (4)$$

$$150 \quad dlon = \begin{cases} 0 & \cos(lat_{nadir}) = 0 \\ \psi & \cos(lat_{nadir}) \neq 0 \end{cases} \quad (5)$$

$$151 \quad \psi = \begin{cases} \arctan\left(\frac{y}{x}\right) & x > 0 \\ \pi + \arctan\left(\frac{y}{x}\right) & y \geq 0, x < 0 \\ -\pi + \arctan\left(\frac{y}{x}\right) & y < 0, x < 0 \\ \frac{\pi}{2} & y > 0, x = 0 \\ -\frac{\pi}{2} & y < 0, x = 0 \\ undefined & y = 0, x = 0 \end{cases} \quad (6)$$

$$x = \cos\left[\frac{d}{R_{\otimes}}\right] - \sin(lat_{nadir}) \cdot \sin(lat_{off-nadir}) \quad (7)$$

$$y = \sin(\phi_v) \cdot \sin\left[\frac{d}{R_{\otimes}}\right] \cdot \cos(lat_{nadir}) \quad (8)$$

d [km] is the distance from the CAR instrument to the off-nadir target and $R_{\otimes}$ is the earth's radius $\approx 6,378.13$ km. The size of the CAR's ground resolution element (GRE), $[lat_{nadir}, lon_{nadir}]$ is a function of the altitude above ground level (h) as well as IFOV of the instrument ($\alpha = 1^\circ \approx 17.45$ mrad):

$$GRE = \alpha \cdot h \quad (9)$$

The ground-projected instantaneous field of view (GIFOV) is then calculated based on the relationship:

$$GIFOV = h \left[\tan\left(\theta_v + \frac{\alpha}{2}\right) - \tan\left(\theta_v - \frac{\alpha}{2}\right) \right] \quad (10)$$

Note that the GRE/GIFOV dimensions perpendicular to the azimuth of off-nadir view remain the same. Each location is also referenced to the WGS-84 datum using a “flat earth” approximation. After establishing the geolocation parameters of each observation (i.e., geographic coordinates, GIFOV, and view-solar geometries), the RTLSR model parameters are then inverted from all available observations on a per grid cell basis. Finally, spatially-distributed (or gridded) fields, each defined by a distinct cell size and GIFOV range, are generated. The end result is a series of multiscale BRDF retrievals derived explicitly from the CAR instrument.

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170 2.3. Inversion strategy

171 For the BRDF inversion, we adapted the operational Moderate Resolution Imaging Spec-
172 troradiometer (MODIS) BRDF/albedo algorithm to fit atmospherically-corrected surface BRF

173 data from CAR at any spectral band. The MODIS algorithm makes use of a linear kernel-based
 174 model – the semiempirical reciprocal RossThick-LiSparse (RTLSR) model (Wanner et al. 1995;
 175 1997; Lucht et al. 2000), which takes the form

$$\begin{aligned}
 BRDF(\theta_s, \theta_v, \Delta\phi, \lambda) &\cong R(\theta_s, \theta_v, \Delta\phi, \Lambda) \\
 &= f_{iso}(\Lambda) + f_{vol}(\Lambda)K_{vol}(\theta_s, \theta_v, \Delta\phi) \\
 &\quad + f_{geo}(\Lambda)K_{geo}(\theta_s, \theta_v, \Delta\phi, P_4, P_5)
 \end{aligned}
 \tag{11}$$

177 where:

$$K_{vol} = \frac{(\pi / 2 - \xi) \cos \xi + \sin \xi}{\cos \theta_s + \cos \theta_v} - \frac{\pi}{4}
 \tag{12}$$

$$\cos \xi = \cos \theta_s \cos \theta_v + \sin \theta_s \sin \theta_v \cos \Delta\phi
 \tag{13}$$

$$\begin{aligned}
 K_{geo} &= \frac{1 + \sec \theta'_s \sec \theta'_v + \tan \theta'_s \tan \theta'_v \cos \Delta\phi}{2} \\
 &\quad + \left[\frac{t - \sin t \cos t}{\pi} - 1 \right] (\sec \theta'_s + \sec \theta'_v)
 \end{aligned}
 \tag{14}$$

$$\cos^2 t = \min \left\{ \left[\frac{P_4}{\sec \theta'_v + \sec \theta'_s} \right]^2 \left[D^2 + (\tan \theta'_v \tan \theta'_s \sin \Delta\phi)^2 \right], 1 \right\}
 \tag{15}$$

$$\tan \theta'_x = P_5 \tan \theta_x \quad ; \quad x = v \text{ or } s
 \tag{16}$$

$$D = \sqrt{\tan^2 \theta_s + \tan^2 \theta_v - 2 \tan^2 \theta_s \tan \theta_v \cos \Delta\phi}
 \tag{17}$$

184 where the wavelength for the narrowband instruments of interest is here defined over the wave-
 185 band Λ with limits $[\Lambda_{min}, \Lambda_{max}]$. Parameter $f_{iso}(\Lambda)$ is the isotropic scattering component and
 186 equivalent to a nadir-view ($\theta_v = 0$), zenith-sun ($\theta_s = 0$) reflectance retrieval. Parameter $f_{geo}(\Lambda)$ is
 187 the coefficient of the LiSparse-Reciprocal geometric scattering kernel K_{geo} , derived for a sparse
 188 ensemble of surfaces casting shadows on a Lambertian background (Li and Strahler 1992). Pa-
 189 rameter $f_{vol}(\Lambda)$ is the coefficient for the RossThick volume scattering kernel K_{vol} , so called for its

assumption of a dense leaf canopy (Ross 1981). $\Delta\phi$ is the relative azimuth angle ($\Delta\phi = \phi_s - \phi_v$) (where subscript s and v denote solar and view azimuth, respectfully) and ξ is the scattering (or phase) angle between sun and view directions. The variable h is the height at which a crown center is located, b is the vertical half-axis of the modeled ellipsoid, and r is its horizontal radius. Based on previous experiments, the dimensionless crown relative height ($P_4 = h/b$) and shape ($P_5 = b/r$) parameters have been fixed at $h/b = 2$ and $b/r = 1$ to invert the angular radiance data from MODIS (Wanner et al. 1995; Privette et al. 1997).

In order to invert Eq. (11) for given reflectance observations $\rho(\theta_s^i, \theta_v^i, \Delta\phi^i, \Lambda)$ ($i = 1, \dots, n$) over a given grid cell, we need to minimize $\delta e^2 / \delta f_k(\Lambda)$ of a least squares error function

$$e^2 = \frac{1}{n-3} \sum_{i=1}^n \frac{(\rho(\theta_s^i, \theta_v^i, \Delta\phi^i, \Lambda) - R(\theta_s^i, \theta_v^i, \Delta\phi^i, \Lambda))^2}{w_i(\Lambda)} \quad (18)$$

to establish the analytical solution for the RLTSR BRDF model parameter values $f_k(\Lambda)$,

$$f_k(\Lambda) = \frac{\sum_{i=1}^3 \left\{ \sum_{j=1}^n \frac{\rho(\theta_s^j, \theta_v^j, \Delta\phi^j, \Lambda) K_i(\theta_s^j, \theta_v^j, \Delta\phi^j, \Lambda)}{w_j(\Lambda)} \right\}}{\times \left(\sum_{l=1}^n \frac{K_l(\theta_s^l, \theta_v^l, \Delta\phi^l, \Lambda) K_k(\theta_s^l, \theta_v^l, \Delta\phi^l, \Lambda)}{w_l(\Lambda)} \right)^{-1}} \quad (19)$$

where $w_j(\Lambda)$ is the weight for the j th observation at waveband Λ . For any given CAR retrieval scenario, a full BRDF model inversion is attempted if at least 7 observations are available. Each observation is evaluated to discard outliers and additional checks (e.g., establishing the model-fits RMSE and angular sampling uncertainty) are performed to assure that the RLTSR model parameters are positive.

Fig. 2 illustrates the shapes of the RossThick (K_{vol}) and LiSparseReciprocal (K_{geo}) kernels, based on the CAR atmospherically-corrected BRF data from the CART site, described in Section

3. Note that the behavior of the two kernels is different in nature over the full angular range of CAR observations. While they are not perfectly orthogonal functions, K_{vol} and K_{geo} are sufficiently independent to allow for a stable recovery of the RTLSR model parameters for many viewing and illumination conditions. The absence of excessive kernel-to-kernel correlation is key to reliable BRDF model inversions (Lucht et al. 2000).

Finally, the model-fits error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^n \left(\rho(\theta_s^i, \theta_v^i, \Delta\phi^i, \Lambda) - R(\theta_s^i, \theta_v^i, \Delta\phi^i, \Lambda) \times w_i(\Lambda) \right)^2}{n-3}} \quad (20)$$

where $w_i(\Lambda)$ is the weight for the i th observation at waveband Λ . Weights are applied using a standard Gaussian-threshold defined by

$$w_i(\Lambda) = p_i(\Lambda) \times s_i(\Lambda) \quad (21)$$

where,

$$p_i(\Lambda) = e^{-\frac{\Delta\phi^2}{2c^2}} + e^{-\frac{(180^\circ - \Delta\phi)^2}{2c^2}} \quad (22)$$

$$s_i(\Lambda) = e^{-\frac{(GIFOV-scale)^2}{2d^2}} \quad (23)$$

$$c = 45^\circ \quad ; \quad d = scale/3.0 \quad (24)$$

The first weight, $p_i(\Lambda)$, depends on the adequacy of the angular sampling across the solar azimuth region or principal plane, where the surface reflectance anisotropy is more sensitive to canopy biophysical characteristics (Privette et al. 1996; Bacour et al. 2002). The second weight, $s_i(\Lambda)$, depends on the degree of spatial correspondence (or representativeness) between the ground-projected instantaneous field of view (GIFOV) and the scale (or grid cell size) being selected (Román et al. 2009). The range of viewing and illumination conditions resulting from

these constraints are intended to produce retrievals that are more sensitive to variability in the structural characteristics of different heterogeneous landscapes.

The angular sampling uncertainty is determined by computing the overall spread (or dispersion, σ_K , of the RTLSR kernels

$$\sigma_K = \left[\frac{\sum_{i=1}^n (K_{vol}(i) - \bar{K}_{vol})^2}{n-1} + \frac{\sum_{i=1}^n (K_{geo}(i) - \bar{K}_{geo})^2}{n-1} \right] \quad (25)$$

Since the RTLSR kernels provide different geometric expressions for a particular type of BRDF, it should follow that the larger the spread (σ_K), the more adequate the angular sampling under a given sun-view geometry.

Both the RMSE and angular sampling uncertainty (σ_K) are computed to establish retrieval confidence. Only if the observations pass all of these evaluations is a full inversion performed to establish the RTLSR kernel values that provide the ‘best fit’ (RMSE) estimate. For those cases with insufficient observations ($i < 7$), or a poor fit, a magnitude inversion is performed rather than a full model inversion. Note that, unlike the MODIS magnitude inversion strategy over snow-free environments (which leverages a global database of archetypal anisotropic models of MODIS-derived representation of seasonal BRDF), this retrieval scheme reutilizes the CAR BRDF retrievals obtained during the same flight period to process those areas where a full retrieval couldn’t be made. An ancillary database derived from high-quality, coincident, and co-located surface BRDF data is then parameterized with area-based proportions of land cover type to obtain a set of archetypal BRDF shapes (*cf.*, Section 3). Consequently, by assuming that surface BRFs scale linearly in a spatial sense (Lewis 1995), a full range of mixed BRDF patterns can be reconstructed using the following equation:

$$R(\theta_s, \theta_v, \Delta\phi, \Lambda) \cong \sum_{k=1}^3 f'_k(\Lambda) K_k(\theta_s, \theta_v, \Delta\phi) \quad (26)$$

where

$$f'_k(\Lambda) = \sum_{j=1}^n c_j f_{k_j}(\Lambda) \quad (27)$$

and c_j is the proportional weight of each land cover type ($j = 1, \dots, n$) within a given CAR grid cell. Accordingly, magnitude inversions were supported by a “first-guess” estimate of the general BRDF shape for a spatially heterogeneous landscape, and then constrained by the available observations. With the exception of water-contaminated regions, gap-filled retrievals were also obtained for areas without available observations.

2.3.1. Albedo retrieval

Once appropriate RossThick-LiSparseReciprocal (RTLSR) BRDF model parameters have been retrieved, the directional-hemispherical reflectance (DHR), or black-sky albedo (BSA), are computed at any desired solar zenith angle by integration over all view zenith angles. A further integration over all illumination angles results in a bihemispherical reflectance (BHR), or white-sky albedo (WSA), under isotropic illumination. These two quantities can be determined from Eqn. (28-29):

$$BSA(\Lambda, \theta_s) = \sum_k f_k(\Lambda) \cdot h_k(\theta_s) \quad (28)$$

$$WSA(\Lambda) = \sum_k f(\Lambda)_k \cdot H_k \quad (29)$$

where: $h_k(\theta_s)$ is the integral of the BRDF model kernels k over a given view zenith and view-sun relative azimuth angle; H_k is the integral of h_k over a given solar zenith angle θ_s ; and $f_k(\Lambda)$ are the BRDF kernel model parameters k . It should be noted that the black-sky and white-sky albedo

quantities are intrinsic to a specific location and are governed by the character and structure of its land cover (Schaaf et al. 2008).

The CAR retrieval scheme can be extended to acquire other multi-view angle data of interest to studies of the photosynthetic and structural characteristics of vegetation covers and their phenological state (e.g., Nadir BRDF-Adjusted Reflectances and BRDF shape indicators). For the purposes of this study, however, only surface BRF retrievals (i.e., obtained from inversion of RTLSR BRDF model parameters) were examined. We can now look at the measurements used to test the new retrieval scheme.

3. Measurements

The CAR data were selected from the Cloud and Land Surface Interaction Campaign (CLASIC), an extensive field campaign conducted in the summer of 2007 in Oklahoma and Kansas with a primary emphasis on the US Southern Grain Plains (SGP; Fig. 3a). The intense observing period was from June 9-30, 2007 based out of Ponca City, Oklahoma. In addition to the large-scale soil moisture measurements conducted throughout the CLASIC experiment, land cover surveys, vegetation measurements, and surface characterizations were also conducted to develop detailed vegetation water content and land cover imagery (Cosh 2007). These records were combined with medium-to-high spatial resolution multispectral satellite imagery – i.e., a 2.4 m IKONOS scene (GeoEye 2006), three Landsat 30 m scenes and eight Advanced Wide Field Sensor (AWiFS) 56 m scenes (NRSA 2003) – to create a 10 km² land cover map with an overall classification accuracy of 92% (relative to ground surveys; Fig. 4a). The effective spatial resolution of the CLASIC land cover map is 2.4 m; although it includes surface characterizations collected at 30 m and 56 m, as well as polygon datasets extracted from land cover surveys. The

total number of classes was reduced by 10, according to survey results acquired during the period coinciding with the CAR measurements.

Onboard the Jetstream-31 aircraft, the CAR instrument was used to acquire multiangular and multispectral observations under different sky conditions (Fig. 5a,b). Flights were designed to cover four major surface conditions across the SGP, including crops, bare soils, and pasture at the CART site, 36.60°N, 97.48°E, grasslands at the Little Washita Watershed, 35.044°N, 97.914°W, irrigated crops at the Fort Cobb Watershed, 35.15°N, -98.47°E, and broadleaf deciduous canopies at the Forest Site, 35.615°N, -96.07°E) (Cosh 2007). The present study focuses on the events surrounding the CART site, which is heavily instrumented and dominated by cattle pasture, bare soils, and winter-wheat fields (*cf.*, Fig. 3).

To acquire BRDF measurements, the aircraft flew a clockwise circular pattern above the surface (Fig. 5c) repeatedly, and at different altitudes ranging from ~0.2 to <8 km. At an aircraft bank angle of 20°, the plane takes roughly 2–3 min to complete an orbit. Among the unique features of the CAR is the fact that the instrument observes the reflected solar radiation at a fine angular resolution defined by an instantaneous field of view of 1°. It is normally set to scan from nadir all the way to the zenith (*cf.*, Fig. 2a), but can also be set to observe the entire downwelling scattered radiation field at approximately half-degree intervals through its 190° aperture at a rate of 100 scans per minute. Therefore, the CAR collects between 76,400 and 114,600 directional measurements of radiance per channel per complete orbit, which amounts to between 687,600 and 1,031,400 measurements per orbit for nine channels.

We selected the J-31 flight on 24 June 2007, Flight # 1928, over the CART site because of favorable clear-sky conditions. A complete description of this and other CAR flights, including flight summaries (*i.e.*, path, timing, and measurements, imagery, and mission details) can be

found on the CAR web site (<http://car.gsfc.nasa.gov/>). Angular measurements were taken at several heights above ground level (i.e., 200 m, 600 m, 2000 m, and ~4000 m). This resulted in 1,619,543 individual BRDF measurements at view zenith angles from nadir to 75° off-nadir, and at spatial resolutions ranging from 3 m – 500 m. We performed atmospheric correction using each observation’s unique viewing (i.e., $0^\circ \leq \Delta\phi \leq 180^\circ$; $0^\circ \leq \theta_v \leq 75^\circ$) and illumination geometries (i.e., $48^\circ \leq \theta_s \leq 72^\circ$), under a non-Lambertian surface, and for corresponding height above ground level (i.e., from 0.2 km – 4.0 km). Other quantities used for the radiative transfer calculations include: (1) total column $\tau_{0.55\mu m} = 0.150$ (0.141 above the aircraft when flying at ~0.2 km above the surface); (2) total column $H_2O = 1.42 \text{ g cm}^{-2}$ (0.62 g cm^{-2} above the aircraft); and (3) ozone column amount $O_3 = 344 \text{ DU}$.

A database of archetypal BRDF shapes derived from Flight #1928 measurements, and parameterized with land cover data, was also created. This was achieved by: (1) deriving GIFOV-specific values of percent land cover by using the CLASIC land cover map as the base layer; (2) extracting those observations that formed a single (or dominant) surface condition; and (3) averaging those remaining measurements that were acquired at $\pm 15^\circ$ off the principal plane and observed under the similar view-solar conditions (i.e., $\pm 1^\circ$). We defined dominant surface conditions as those with a fractional cover of $\geq 75\%$ and we limited water-contaminated areas to $< 5\%$. To the extent possible, areas comprised by ‘water’ and ‘land/water mix’ classes (*cf.*, Fig. 4a) were excluded from this analysis. This was done to reduce classification errors associated with changing weather conditions. The observations that passed the above-mentioned screening tests were then used to invert the RTLSR BRDF model parameters and obtain best-fit (RMSE) estimates across the principal plane. Under this premise, the BRDF model parameters acquired using the above mentioned screening process were used to calculate the weighted average (based on

the band-specific ‘best fit’ RMSE estimate) for each representative land cover class identified across the CART site during the CLASIC experiment (Table 1).

Spatially-distributed BRDF retrievals were derived from the Flight #1928 RossThick-LiSparseReciprocal (RTLRSR) model parameters using three different grid sizes. Fig. 6 illustrates the results for a 10 km² area surrounding the CART site. Different panels represent the RTLRSR kernel values, $f_{iso}(\Lambda)$, $f_{vol}(\Lambda)$, and $f_{geo}(\Lambda)$, for CAR channels $\Lambda = 0.682 \mu\text{m}$ (Fig. 6a) and $\Lambda = 0.870 \mu\text{m}$ (Fig. 6b). Each retrieval is defined by a distinct cell size (or spatial scale) and ground-projected instantaneous field of view (GIFOV) range. The three sampling intervals (i.e., 30 m, 60 m, and 240 m) were selected on the basis of how CAR measurements obtained at different GIFOVs were observed similarly in terms of angular sampling. This is demonstrated in Fig. 7, which shows the distribution of surface-level BRFs from Flight #1928 as a function of GIFOV, view zenith angle, solar zenith angle, and relative azimuth angle. One can see that, irrespective of the spatial scale, CAR observations are sampled across a broad range of viewing and illumination conditions. A slight divergence occurs at observations with GIFOVs > 90 m. Due to a limited flight ceiling of ~4 km, the lowest view zenith angle achieved across this particular range was ~30° (Fig. 7b). While this limited view angle range may somewhat affect the quality of the BRDF model inversions at moderate spatial resolutions (i.e., scale = 240 m), a detailed characterization of the uncertainties (as described in Section 2.3) was performed to determine whether each retrieval was accessing enough information of the theoretical reflectance space to accurately retrieve the RTLRSR model parameters. As a result, retrievals are supported by extensive quality assurance information to make sure that the output is appropriate for validation and inter-comparison purposes.

Fig. 6c illustrates the spatial distribution of the Quality Assurance (QA) Science Data Set (SDS) generated by the retrieval scheme. This layer provides basic QA for BRDF model inversion data, with green pixels denoting high-quality full inversion retrievals, red pixels denoting moderate quality magnitude inversion retrievals, and yellow pixels denoting gap-filled values (i.e., using the ancillary BRDF database and employing the linear-mixture assumption – *cf.*, Section 4.1) for areas with insufficient (< 1) observations. Unless a sufficient number of observations (> 7) were available, water-contaminated areas (i.e., black pixels) were not processed. Notice that the spatial distribution of high-quality (or full inversion) retrievals varies according to the scale of sampling. The 30 m BRDF fields were primarily centered on the CART site, but as the aircraft moved to higher altitudes (i.e., to acquire surface BRFs at GIFOVs > 45 m), more observations were acquired northwest of the site. Despite this effect, a sufficient number of full inversion retrievals (totaling an area of ~ 4.5 km²) were observed similarly in terms of spatial and angular sampling. Note that, since the gap-filled BRDF retrievals from CAR are spatially-invariant by nature (i.e., regardless of scale, the resulting mixture of BRDFs originate from the same source) these retrievals were only used to improve the spatial coverage. Accordingly, only full inversion retrievals were used to perform the multiscale comparisons and uncertainty analyses presented in the discussion (i.e., Section 4.0).

During the CLASIC experiment, the number of cloud-free acquisitions from the MODIS sensors onboard the Terra and Aqua satellites was impacted by the anomalous rainfall (Bindlish et al. 2009; Heathman et al. 2009). Since the MODIS Collection 5 BRDF/albedo algorithm assumes the surface reflectance anisotropy to remain stable for a period of 16 days, high-quality full inversion retrievals were obtained for less than 20% of the total 10 km² study area. To address the extensive data gaps caused by persistent clouds, gap-free, quality-enhanced retrievals

(Zhang 2008) were used to reconstruct the surface reflectance anisotropy of the CART site during the CLASIC experiment. By applying temporal fitting techniques based on vegetation yearly development and spatial fitting techniques to the MODIS RTLSR BRDF model inversions – similar to the techniques previously applied to the MODIS albedo products (Moody et al. 2008) and the MODIS leaf area index (LAI) products (Gao et al. 2008) – this approach was able to compensate for missing data and provide an estimate of the surface reflectance anisotropy for situations under cloud-contaminated conditions. It is important to note, however, that despite the usefulness of this retrieval method in maximizing the influence of available observations, the resulting BRDF fields can only provide a close (but not exact) representation of the surface conditions during the CLASIC experiment. Thus it is difficult to determine, through this approach, whether rapidly changing surface conditions resulting from flooding and agricultural activities are being captured completely and accurately throughout this period. Nevertheless, a judicious use of available in-situ and ancillary datasets should provide sufficient constraints to address land cover/use changes resulting from events following Flight #1928.

4. Discussion

The purpose of this section is to demonstrate results from the new BRDF retrieval scheme with inversion of data from the CLASIC experiment. We will also examine the uncertainties in BRDF retrievals resulting from utilization of a priori knowledge in kernel-driven BRDF model inversions, explore the spatial scaling assumptions, and finally compare the CAR and MODIS BRDF retrievals.

4.1. *A priori knowledge in kernel-driven BRDF model inversion*

Routine production of land surface BRDF retrievals is often achieved by compiling (or relying on) a global database of archetypal BRDFs that seeks to describe the natural variability of terrestrial ecosystems, at several seasons whenever possible (Bicheron and Leroy 2000; Strugnell et al. 2001; Lacaze et al. 2002; Bacour and Bréon 2005). In general, the BRDF associated with each location is assumed to be comprised of either a “complete” linear mixture of different ecosystem types or “dominated” by a single ecosystem type. In other cases, target-specific BRDF knowledge is used to supplement available observations and improve the quality of a retrieval. For instance, Jin et al., (2002) has leveraged the BRDF model parameters derived from Multi-angle Imaging SpectroRadiometer (MISR) surface BRFs to bring additional information to the MODIS retrieval scheme; especially when the MISR observations were close to the principal plane. In either case (i.e., using land cover type-related knowledge or target-specific knowledge), a priori information is being used to indicate when retrieved RTLSR model parameters (or albedos) are outside the expected bounds. These approaches are based on Bayesian inference theory, which is considered to be the best way to make use of a priori knowledge to yield a posteriori estimates of unknown BRDF model parameters (Li et al. 2001).

We now examine the efficiency of BRDF retrievals employing a priori archetypal BRDF shapes to describe the surface anisotropy as either: (1) a linear-mixture of different ecosystem types; or (2) a single (or dominant) ecosystem type. The goal of this exercise is to provide additional constraints into the appropriate spatial length scales and degree of subpixel detail necessary to retrieve the BRDF of target using land cover type-related knowledge. Using data from Flight #1928, we computed the model-fits error (RMSE) of high-quality full inversion retrievals acquired directly from CAR data and then established the relative departure of RMSE values

(%) using the “linear-mixture” (i.e., $\Delta\text{RMSE} = \text{RMSE Linear-Mixture} - \text{RMSE Full Inversion}$) and “dominant” (i.e., $\Delta\text{RMSE} = \text{RMSE Dominant} - \text{RMSE Full Inversion}$) approaches (Fig. 8; Table 2). Since the RMSE establishes the deviation of the RTLSR model-fits from actual surface BRF measurements, this evaluation should result in uncertainty estimates that are of equal (or comparable) magnitude to those derived through direct means (i.e., from high-quality, full inversion retrievals). Thus, if BRDF retrievals employing a priori archetypal BRDF shapes can truly characterize the reflectance anisotropy of mixed agricultural landscape, then the cumulative distribution of relative RMSE differences (%) should follow a normal pattern with a limit (ΔRMSE) equal or close to zero. Note that, based on the scaling principles of linear BRDF modeling theory, this should apply regardless of the scale at which the assumption is being examined.

Results confirm that the relative RMSEs for a priori archetypal BRDF shapes are moderately higher than the full-inversion results. The uncertainties are also consistently larger in the shorter wavelengths ($\lambda \leq 0.682 \mu\text{m}$) and smaller at the longer wavelengths ($\lambda \geq 0.870 \mu\text{m}$). Improvements in the range of 0.5% – 6.5% (relative RMSE terms) were also documented when replacing the “single-biome” BRDFs with the “linear-mixture” BRDFs. Finally, with the exception of the blue CAR channel ($\lambda = 0.472 \mu\text{m}$), retrievals at coarser spatial resolutions (i.e., $> 90 \text{ m}$) were consistently of higher quality than those retrieved at finer spatial resolutions (i.e., $< 45 \text{ m}$). Thus, while the utilization of a priori knowledge obtained at fine spatial scales is usually assumed to capture the angular variability of spatially heterogeneous environments, these results suggest that the assumption of linearity in kernel-driven BRDF models may in fact be most appropriate at “landscape-level” scales (i.e., $> 90 \text{ m}$).

4.2. Spatial scaling assumption

Due to constraints of instrumentation, platform, and the logistically-challenging nature of airborne data collection and processing, most airborne multiangle experiments have been unable to acquire spatially-distributed BRDF data at landscape-level scales > 90 m (Walthall et al. 2000). To get around this problem, previous studies have stipulated that in-situ measurements acquired at scales larger than the intrinsic length scale of the surface should represent the BRDF patterns observed at larger spatial scales (Brown de Colstoun et al. 1996; Leroy et al. 1997; Qin and Gerstl 2000). In general, a GIFOV ≥ 15 m has been routinely used to provide an adequate sample of the BRDF at subpixel scales (Pelgrum et al. 2000; Chopping et al. 2002). Thus, up to now, the only alternative has been to “simulate” a larger GIFOV by convolving fine-resolution estimates with the point spread function (PSF) of a moderate resolution satellite sensor. For instance, the AirMISR instrument with an effective pixel size of 27.5 m at nadir, which grows at steeper angles (Diner et al. 1998a), is upscaled to match MISR’s effective spatial resolution of 275 m (Gobron et al. 2002; Pinty et al. 2002). The same spatial scaling principle is applied to the MODIS Airborne Simulator (MAS) (King et al. 1996), which has an effective pixel size of 50 m, and is upscaled to MODIS spatial resolutions >250 m. The assumption, then, is that the aggregated BRDF datasets should scale linearly in a spatial sense (Roujean et al. 1992; Lewis 1995). However, because the scale for shadowing and clumping effects depends on spatial resolution, such “upscaled” results can lead to different spatial and structural patterns (d’Entremont et al. 1999; Walthall et al. 2000). As a result, high spatial resolution BRDF retrievals that are convolved to a larger GIFOV may still be conditioned by the BRDF patterns observed at plot-level scales. To illustrate this effect, Fig. 9 illustrates the spatial and angular characteristics of CAR and MODIS Collection 5 BRDF model inversions (MCD43A1). Each false-color composite de-

scribes the spectral BRF response at 0.870 μm (Red), 0.682 μm (Green), and 0.472 μm (Blue),
 for five different view zenith angle intervals measured across the principal plane (i.e., $\Delta\phi = 0^\circ$)
 and using a SZA = 60° . Negative VZA values represent the backscattering while positive values
 represent the forward scattering. In the back scattering direction, pastures and crop fields show a
 strong directional response in the NIR (as seen in bright-reds and pink colors); while bare soils
 show a lower directional response (as seen by shades of pale-blue and cyan). Conversely, in-
 creased shadowing in the forward scattering results in a lower response in the red and NIR (as
 seen in dark purple and magenta tones), which then increases the overall contrast of bare soils (as
 seen in dark and bright shades of cyan). The histograms in Fig. 10 illustrate the distribution for
 each of the view-angle geometries examined in Fig. 9, using four discrete wavelengths from
 0.472 μm (0.465 μm for MODIS) to 1.219 μm (1.241 μm for MODIS). Results show a good de-
 gree of correspondence between CAR and MODIS BRFs at view angles closer to nadir (i.e., -30°
 $\leq \text{VZA} \leq +30^\circ$), with improved results for wavelengths $\leq 0.682 \mu\text{m}$. However, at high view ze-
 nith angles, the spread of the distribution in the BRF tends to be narrower at spatial scales $\leq 60 \text{ m}$
 and broader at scales $\geq 240 \text{ m}$. At landscape-level scales, this results in higher BRF values across
 the backscattering and lower BRF values across the forward scattering directions. Conversely, at
 scales $\leq 60 \text{ m}$, vegetated areas exhibit a strong directional response in the forward scattering, and
 (with the exception of the 1.219 μm channel) appear darker in the backscattering. These scaling
 effects may result from distinct spatial and structural BRDF patterns, including: (1) subpixel dif-
 ferences in the BRDF (e.g., row and close-grown crops or mosaics of crops with natural vegeta-
 tion) observed at spatial resolutions $> 90 \text{ m}$, which decreases the overall slope of the BRDF
 shape at moderate spatial resolutions; (2) the influence of specular reflection and transmission of

light at spatial resolutions ≤ 60 m; and (3) the fundamental scales of shadowing for foliage and canopy components manifested at spatial resolutions > 90 m.

In order to quantify the uncertainties that arise when sub-pixel differences in the BRDF are aggregated to a moderate resolution satellite pixel, the quality of MODIS RTLSR surface BRF retrievals was evaluated across spatial scales. Results in Table 3 show that the MODIS retrievals are more consistent with CAR-derived BRFs at moderate spatial resolutions (i.e., scale = 240 m). The quality of these direct “moderate pixel-to-moderate pixel” comparisons resulted in APU units that were 1.15% more accurate, 3.59% more precise, and 0.005 less uncertain. While the finer scale CAR BRFs (i.e., scale = 30 m) were, at times, as consistent as the 240 m BRDF fields, the intermediate results (i.e., scale = 60 m) were not as reliable. The most significant improvement resulted from the ability of moderate resolution retrievals from CAR to capture the range of mixed BRDF patterns as observed by a MODIS 500 m grid cell. This resulted in more precise (and thus, less uncertain) estimates.

5. Conclusions

In previous aircraft campaigns using a variety of multiangular sensors, e.g., FIFE (Sellers et al. 1988; Sellers et al. 1992), OTTER (Waring and Peterson 1994), HAPEX-Sahel (Goutorbe et al. 1994), BOREAS (Russell et al. 1997a), PROVE (Privette et al. 2000), and SAFARI 2000 (Swap et al. 2002; Privette et al. 2004) it was common to acquire multiangle surface bidirectional reflectance factor (BRF) measurements and then compare them directly against coincident ground and/or satellite data to obtain information on both the structure and functioning of terrestrial ecosystems. As we note, these “point-to-pixel” comparisons are influenced by very distinct spatial and structural patterns, including: (1) subpixel differences in the BRDF observed at spa-

tial resolutions > 90 m; (2) the influence of specular reflection and transmission of light at spatial resolutions < 90 m; and (3) the fundamental scales of shadowing for foliage and canopy components manifested at spatial resolutions > 90 m. These scaling mechanisms, as well as other measurement uncertainties arising from geospatial aggregation of subpixel vegetation structural characteristics, can have potential impacts on the utility of multiangle data and products to characterize the ecological and biophysical state of complex ecosystems. Perhaps the biggest problem thus far has been the lack of adequate in-situ measurements and validation techniques for acquiring spatially-distributed surface BRDF data at the relevant spatial scales at which global land products are commonly utilized. While airborne measurements are commonly used to provide an intermediate scale between plot-level (< 15 m) and landscape-level (> 90 m) measurements, the results from this work confirm that, as a result of the inherent lack of mixed-pixel sampling (i.e., both in spatial and angular sense), such approaches are not as appropriate for multiangle remote sensing studies.

With its unique design (i.e., a 190° swath, 1° IFOV, oversampling every 0.5° along the vertical plane), unparalleled instrument accuracy ($\leq 5\%$), and flight capabilities (i.e., multiple circular patterns achieved at different heights above ground level under clear-sky conditions), NASA's Cloud Absorption Radiometer (CAR) is used to generate spatially-distributed BRDF products at different spatial scales. To demonstrate this capability, a new retrieval scheme was developed and applied to a single flight dataset containing ~ 1.6 million individual surface BRFs obtained at view zenith angles from nadir to 75° off-nadir, and at spatial resolutions ranging from 3 m – 500 m. Results over a 10 km^2 area centered on the well-instrumented CART site were then used to determine whether the ability of kernel-driven BRDF models to detect measures of canopy physiognomy and structure (e.g., through different manifestations of the surface reflectance

anisotropy over the angular range) is independent of the spatial resolution of acquisition. Assessments between BRDF retrievals acquired from CAR at different spatial scales, and between CAR and MODIS (500 m) retrievals, confirm that while BRDF patterns observed at fine spatial resolutions (i.e., ~15 m) are usually assumed to be large enough to capture the intrinsic length scale of the surface, the utilization of a priori knowledge in kernel-driven BRDF model inversions and the spatial scaling assumptions underlying semi-empirical kernel-driven BRDF models (Roujean et al. 1992; Lewis 1995) may in fact be limited to considerably larger scales. Thus, only by acquiring surface BRDF retrievals at “landscape-level” scales (i.e., > 90 m) can a resolution limit be reached whereby the resulting BRDF patterns are still representative of the structural response of complex ecosystems at the scale of moderate resolution satellite sensors. Nonetheless, further research is needed (particularly over landscapes with two-layer mixtures of woody overstory and herbaceous understory) to establish more definitive limits on the accuracy of these scaling assumptions. This would allow us to determine what kind of variability in the BRDF is important at what kind of scales.

With the advent of a new generation of multi-sensor data and products obtained through fusion of high-spatial resolution (e.g., Landsat TM/ETM+) and high-temporal resolution satellite datasets (e.g., MODIS and in the future VIIRS) (Gao et al. 2006; Roy et al. 2008), recent efforts have explored the “MODISization” of nadir-looking satellite sensors to obtain high-resolution (30 m) MODIS-driven surface biophysical products at shorter temporal scales (i.e., from weeks to days). Earlier schemes have taken advantage of the temporal efficiency of MODIS (500 m) BRDF retrievals to (among several things) extrapolate the peak-growing season estimates of LAI and/or derive spatially-complete (or gap-filled) directional reflectance retrievals for missing dates of acquisition. This study demonstrates a unique BRDF retrieval capability that may well

serve research efforts that seek to evaluate and refine the accuracy of these multisensor data and products. As more campaign datasets become available in the near future, BRDF retrievals from CAR will be used to obtain different albedo, angular, and vegetation quantities, including BRDF shape indicators (Hill et al. 2008), foliage clumping index (CI) (Chen 1996), canopy shadow fraction, and top-of-canopy vegetation indexes (i.e., NDVI and EVI) (Tucker 1979; Huete et al. 2002) derived from Nadir BRDF-Adjusted Reflectances (NBAR) (Schaaf et al. 2002). In addition to algorithm refinement and validation exercises, these retrievals can be potentially used to characterize the structural dynamics of complex heterogeneous environments, also providing much needed constraints to model interpolations/extrapolations from multisensor surface biophysical datasets obtained at different spatial scales and time periods.

These reference datasets are also needed for studies seeking to identify systematic differences between satellite sensors that may affect the quality and consistency of long-term Earth system data records. For instance, satellite intercomparisons, while useful in pointing out areas of divergence, both in terms of value and quality assurance, cannot establish what products are correct without an independent benchmark that is able to reproduce the wide range of view-angle geometries and retrieval schemes employed by multiple BRDF/albedo datasets (Muller et al. 2007; Geiger et al. 2008; Rutan et al. 2009; Pinty et al. 2010; Taberner et al. 2010). Without an independent mechanism, these assessments will continue to be limited to some verification of the relative performance.

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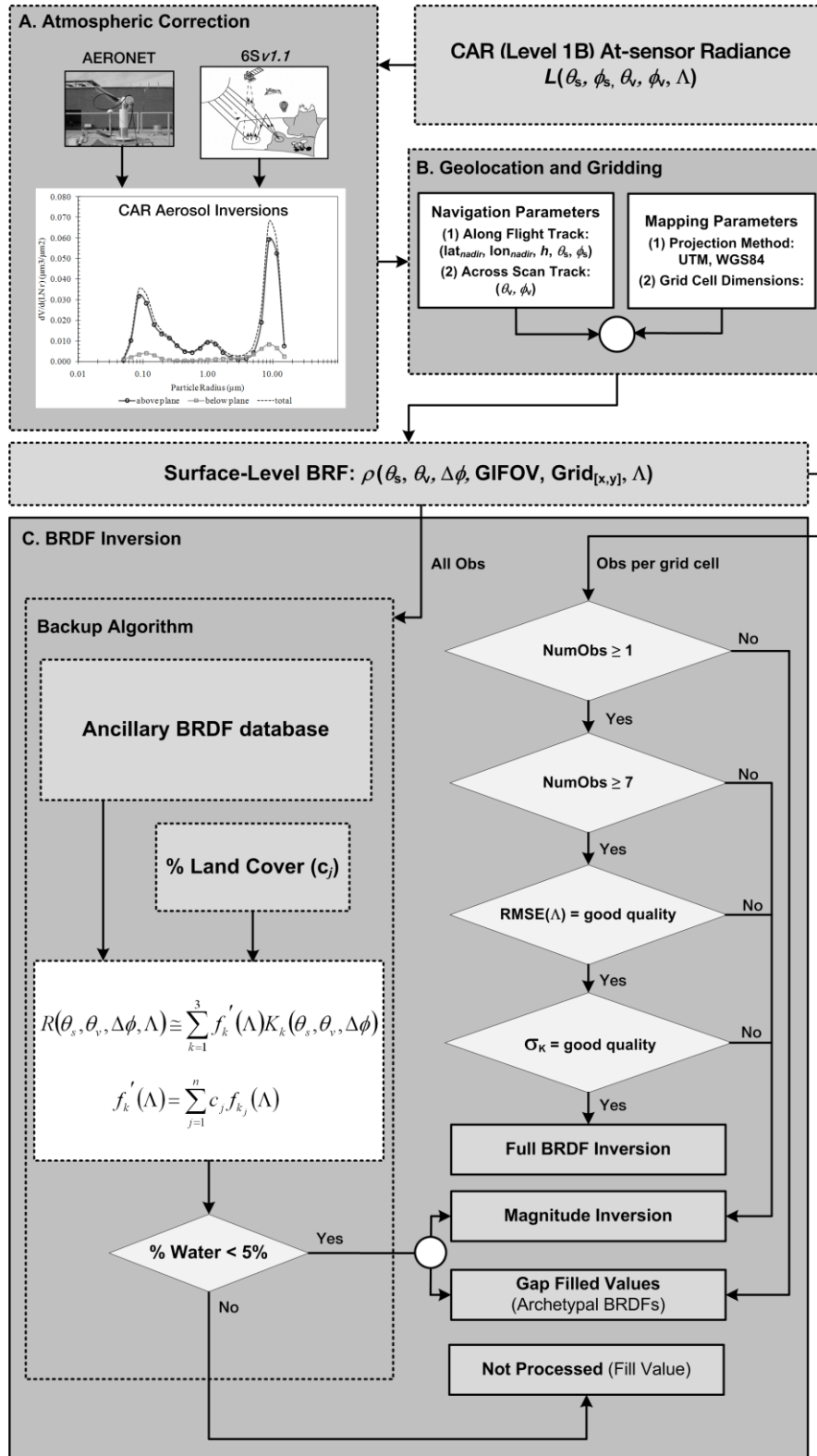


Fig. 1. Processing and data flow diagram illustrating the production of spatially-distributed BRDF retrievals from CAR. The algorithm has three main functional components: (a.) atmospheric correction, (b.) geolocation and gridding, and (c.) BRDF inversion.

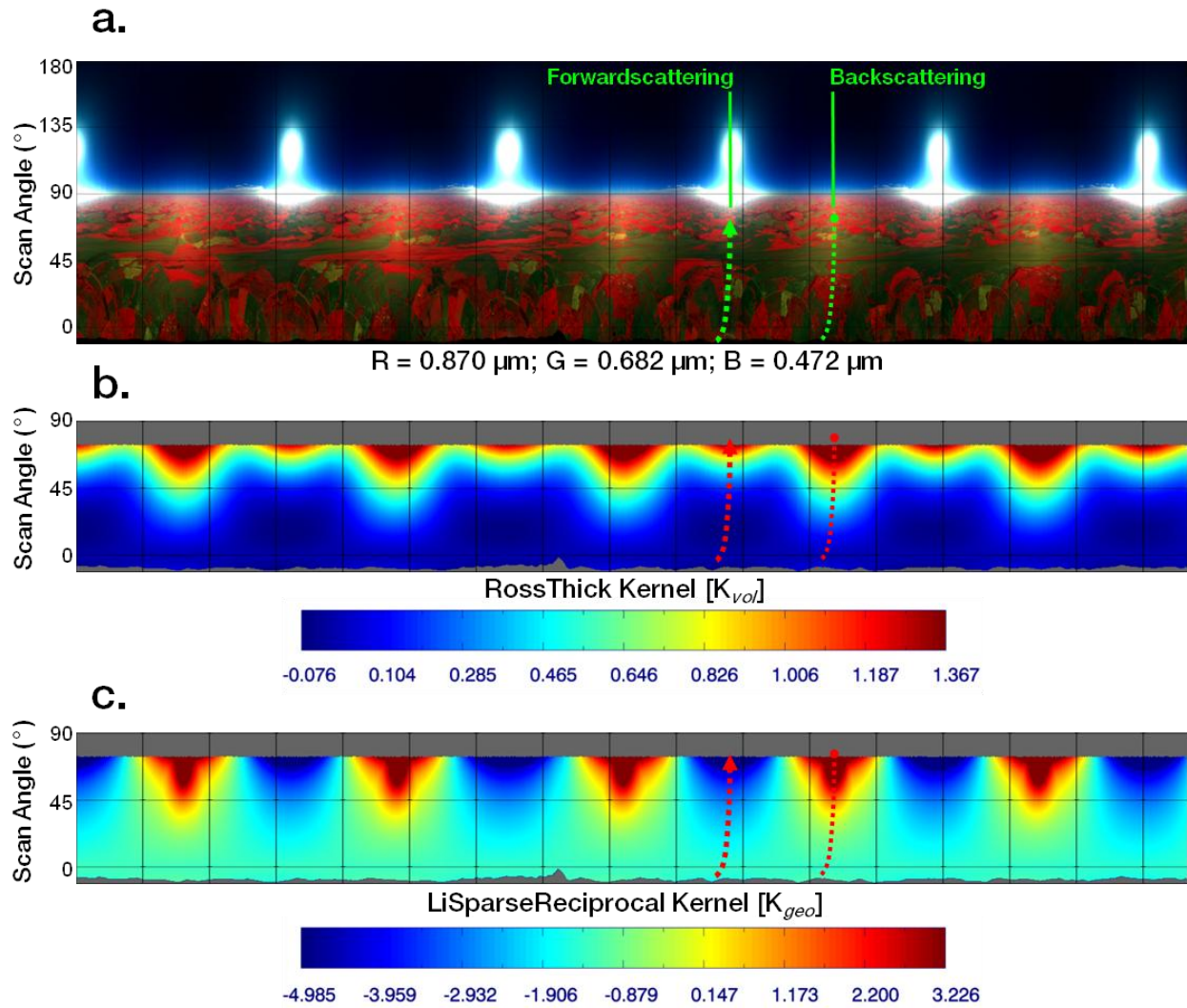


Fig 2. Flight #1928 segment corresponding to a 12 minute period when the Cloud Absorption Radiometer (CAR) was flown at 2.0 km AGL. (a.) False-color surface BRF composite (atmospherically-corrected) for CAR scan angles ranging from zenith to nadir. The five solar disks in full view define the region of forwardscattering (i.e., sun opposite to the CAR instrument) where the presence of specular reflection and transmission of light through the edges of the canopies reaches a maximum. Note the bright areas along the surface located in the mid-regions between solar disks. This is the backscattering, or antisolar or hotspot, direction where all shadows are hidden. The dotted arrows correspond to a transect along the principal plane starting in the backscattering and ending in the forwardscattering direction. Corresponding transects for the RossThick (K_{vol}) and the LiSparseReciprocal (K_{geo}) kernels (b. and c., respectively) are also shown.

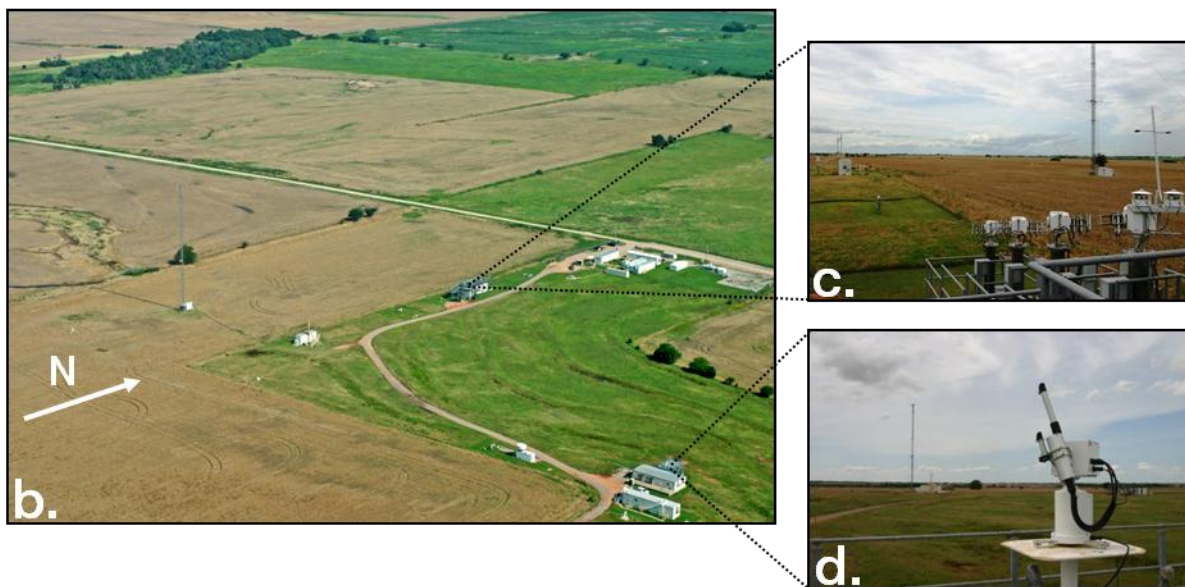
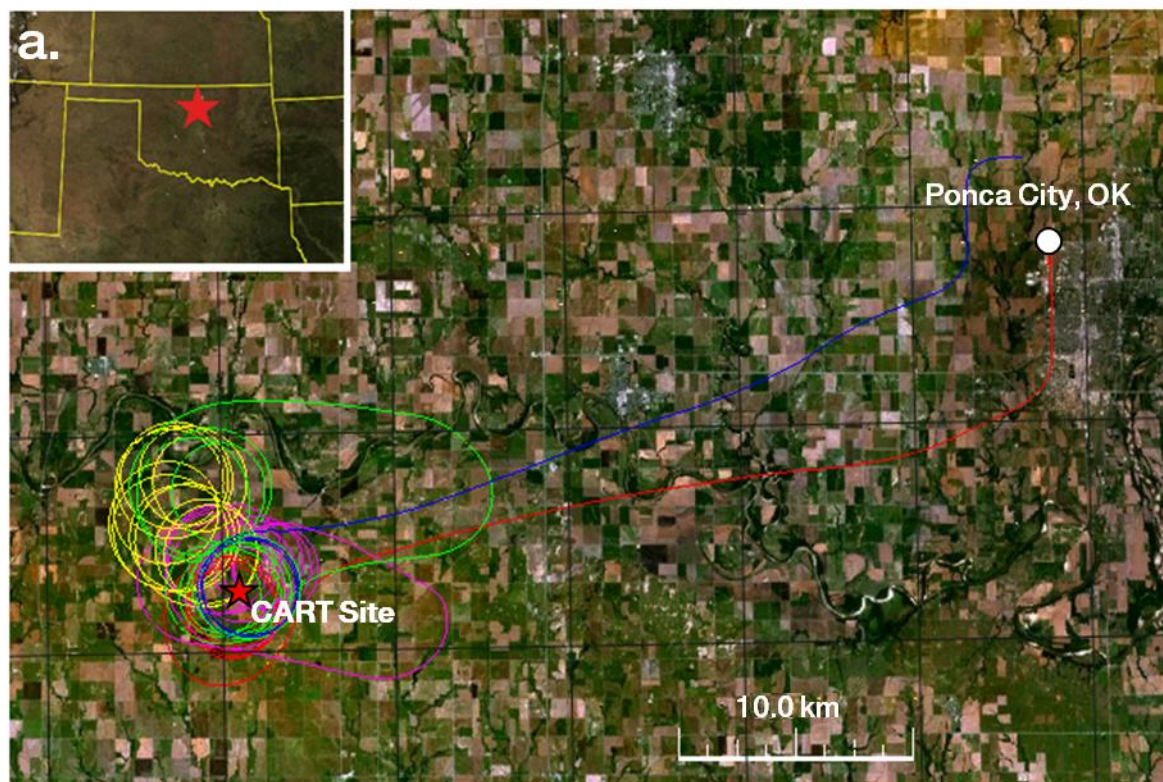


Fig. 3 (a.) Flight #1928 flight track over the U.S. Southern Great Plains Cloud and Radiation Testbed (CART) Site (24 June 2007). The multi-colored track shows the time sequence, with red representing the first 30 minutes of the flight, and then a series of 14-minute time steps starting with magenta, yellow, green, and blue. (b.) Bird's eye view of the CART site taken during Flight #1922 (19 June 2007). (c.) Facing southwest atop the Radiometric Calibration Facility, overlooking the upward-facing pyranometers and the 60 meter radiation tower (20 June 2007). (d.) Facing west atop the Guest Instrument Facility, overlooking the AERONET sun photometer (20 June 2007).

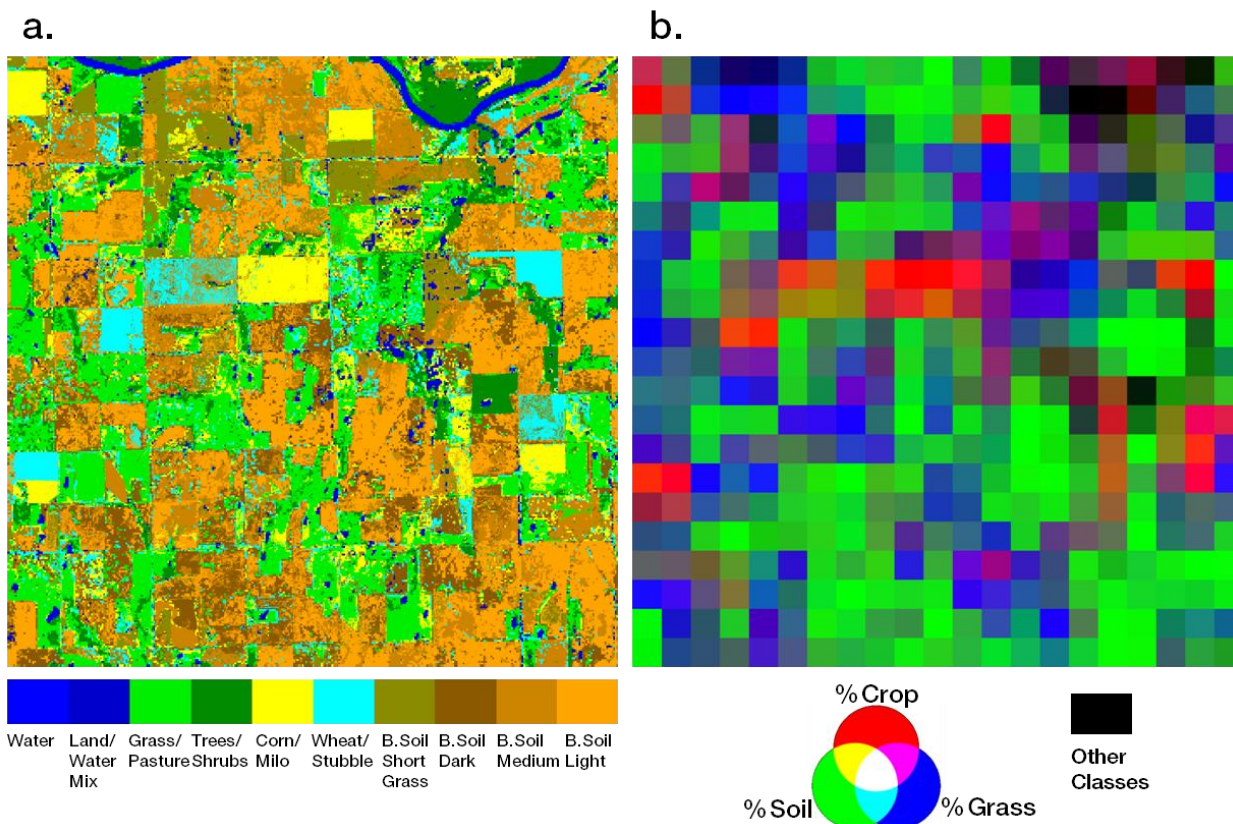
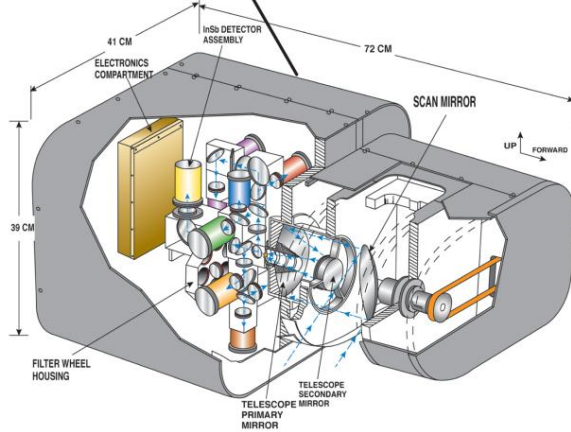


Fig 4. (a.) Land cover types in a 10 km² area surrounding the U.S. Southern Great Plains Cloud and Radiation Testbed (CART) during late June, 2007. The effective spatial resolution of this land cover map is 2.4 m. The overall classification accuracy is ~92% relative to ground-based surveys. The most dominant land cover type (at 55%) is bare soil in various conditions (dark, light, and partially vegetated), followed by pasture/grassland (18%) and corn/milo fields (9%). (b.) Fractional cover estimates (%) of crop (including corn/milo and wheat/stubble classes), pasture, and bare soils, using a 500 m grid cell size.

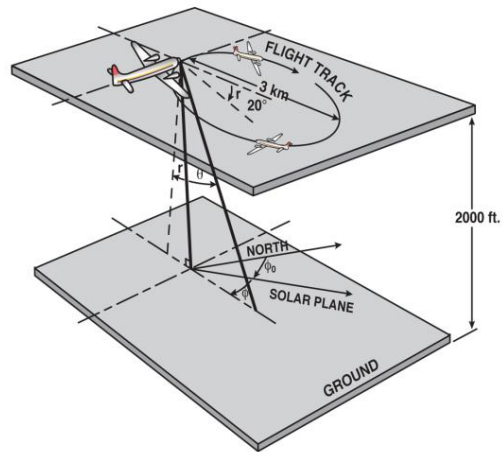
a. Jetstream-31 Aircraft



b. CAR Schematic



c. BRDF Flight Track



d. Cloud Absorption Radiometer (CAR) Parameters

Angular scan range	190°
Instantaneous field of view	17.5 mrad (1°)
Pixels per scan line	382
Scan rate	1.67 scan lines per second (100 rpm)
Spectral channels (μm ; bandwidth (FWHM))	14 ^a (8 continuously sampled and last six in filter wheel): 0.340(0.009), 0.381(0.006), 0.472(0.021), 0.682(0.022), 0.870(0.022), 1.036(0.022), 1.219(0.022), 1.273(0.023), 1.556(0.032), 1.656(0.045), 1.737(0.040), 2.103(0.044), 2.205(0.042), 2.302(0.043)

Fig. 5. (a.) The N22746 aircraft registered to Sky Research Inc. (USA), also known as Jetstream-31 (J-31) in Ponca City Airport, Oklahoma, USA during the 2007 Cloud and Land Surface Interaction Campaign (CLASIC). (b.) Schematic of NASA's Cloud Absorption Radiometer (CAR), which is mounted in the nose cone of the J-31. The CAR measured the spectral and angular distribution of scattered light by clouds and aerosols, and obtained good imagery of clouds and Earth surface features over many areas in the U.S. Southern Great Plains Cloud and Radiation Testbed (CART) Site. (c.) Illustration of a clockwise circular flight track that was used for measuring surface-level bidirectional reflectances. (d.) The CAR has 14 narrow spectral bands between 0.34 and 2.30 μm , and flew 11 missions during CLASIC (Gatebe et al., 2003; King et al., 1986).

Table 1. RTLSR BRDF model parameters, $f_{iso}(\Lambda)$, $f_{vol}(\Lambda)$, $f_{geo}(\Lambda)$, and best-fit RMSE results derived for four discrete wavelengths, from 0.472 μm to 1.219 μm , for each of the representative land covers classes identified across the CART site during the CLASIC experiment.

Surface Type	RTLSR BRDF(0.472 μm)				RTLSR BRDF(0.682 μm)			
	$f_{iso}(\Lambda)$	$f_{vol}(\Lambda)$	$f_{geo}(\Lambda)$	RMSE(Λ)	$f_{iso}(\Lambda)$	$f_{vol}(\Lambda)$	$f_{geo}(\Lambda)$	RMSE(Λ)
Grass/Pasture	0.0303	0.0553	0.0022	0.0108	0.0579	0.0941	0.0058	0.0213
Trees/Shrubs	0.0308	0.0433	0.0030	0.0112	0.0610	0.0649	0.0065	0.0224
Corn/Milo	0.0335	0.0692	0.0005	0.0138	0.0666	0.1074	0.0026	0.0265
Wheat/Stubble	0.0437	0.0419	0.0043	0.0105	0.0916	0.0672	0.0093	0.0240
Bare Soil/Short Grass	0.0500	0.0490	0.0019	0.0124	0.1021	0.0723	0.0031	0.0260
Bare Soil Dark	0.0390	0.0470	0.0014	0.0100	0.0922	0.0839	0.0045	0.0234
Bare Soil Medium	0.0458	0.0544	0.0032	0.0089	0.1050	0.1046	0.0093	0.0191
Bare Soil Light	0.0497	0.0596	0.0027	0.0083	0.1282	0.1253	0.0150	0.0222
Surface Type	RTLSR BRDF(0.870 μm)				RTLSR BRDF(1.219 μm)			
	$f_{iso}(\Lambda)$	$f_{vol}(\Lambda)$	$f_{geo}(\Lambda)$	RMSE(Λ)	$f_{iso}(\Lambda)$	$f_{vol}(\Lambda)$	$f_{geo}(\Lambda)$	RMSE(Λ)
Grass/Pasture	0.3777	0.1108	0.0023	0.0442	0.3357	0.2483	0.0181	0.0378
Trees/Shrubs	0.3444	0.1497	0.0082	0.0479	0.3300	0.2667	0.0268	0.0473
Corn/Milo	0.3712	0.1315	0.0051	0.0535	0.3306	0.2754	0.0136	0.0431
Wheat/Stubble	0.3291	0.2026	0.0154	0.0648	0.3430	0.2559	0.0340	0.0425
Bare Soil/Short Grass	0.3299	0.0890	0.0207	0.0486	0.3663	0.1787	0.0424	0.0419
Bare Soil Dark	0.3201	0.1860	0.0117	0.0504	0.3194	0.2437	0.0157	0.0399
Bare Soil Medium	0.2911	0.1889	0.0184	0.0394	0.3284	0.2285	0.0346	0.0320
Bare Soil Light	0.2972	0.1612	0.0237	0.0387	0.3435	0.2217	0.0369	0.0342

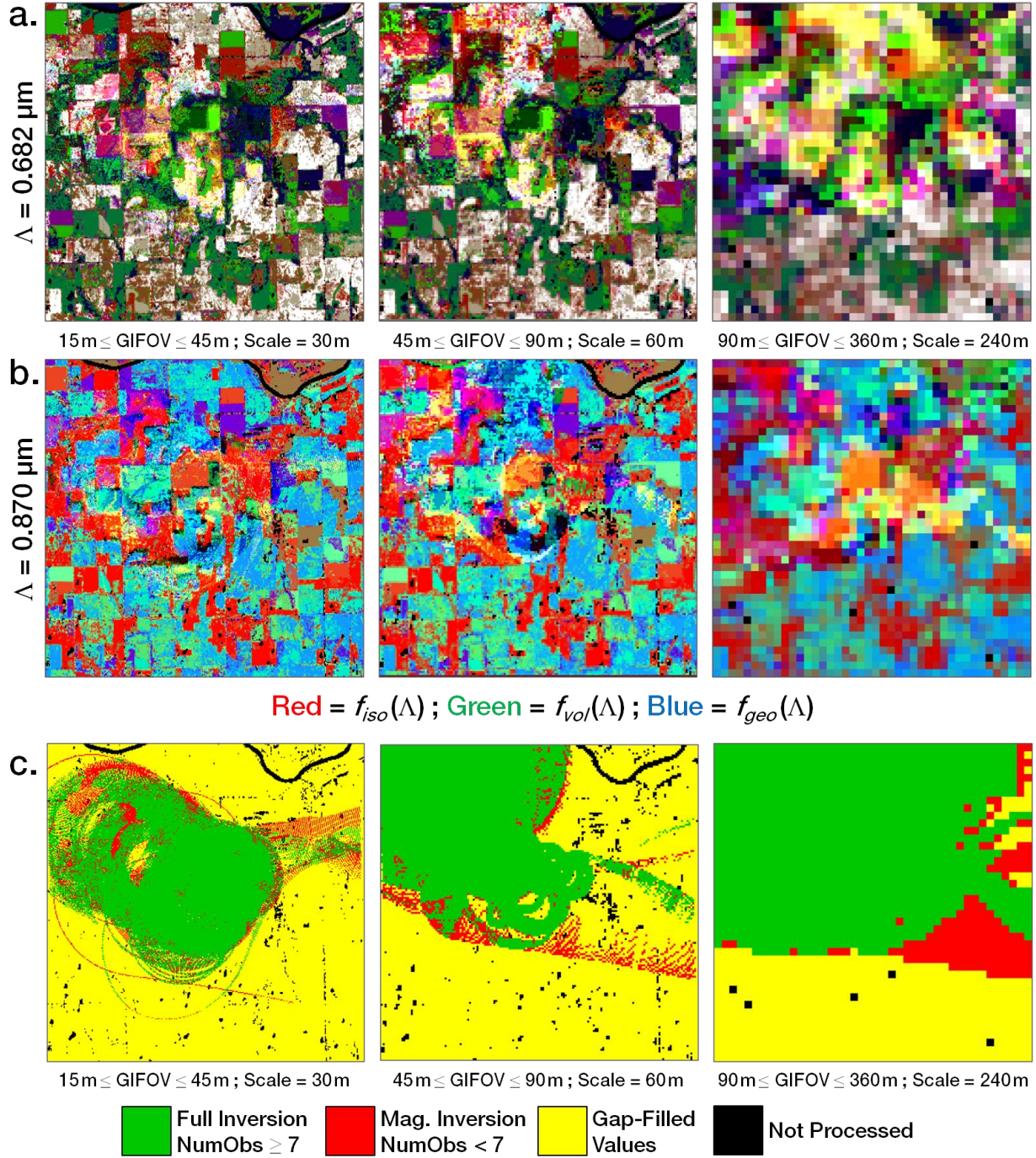


Fig. 6. Cloud Absorption Radiometer (CAR) RTLSR model parameters describing the BRDF at (a.) $\Lambda = 0.682 \mu\text{m}$ and (b.) $\Lambda = 0.870 \mu\text{m}$ for a 10 km^2 area surrounding the U.S. Southern Great Plains Cloud and Radiation Testbed (CART) site during late June, 2007. Each product is defined by a distinct cell size (or scale) (i.e., 30 m, 60 m, and 240 m) and GIFOV range (i.e., $15 \text{ m} \leq \text{GIFOV} \leq 45 \text{ m}$, $45 \text{ m} \leq \text{GIFOV} \leq 90 \text{ m}$, and $90 \text{ m} \leq \text{GIFOV} \leq 360 \text{ m}$). (c.) Per-pixel band-specific BRDF model inversion quality equivalent to the MODIS BRDF/Albedo quality Level 3 product (MCD43A2).

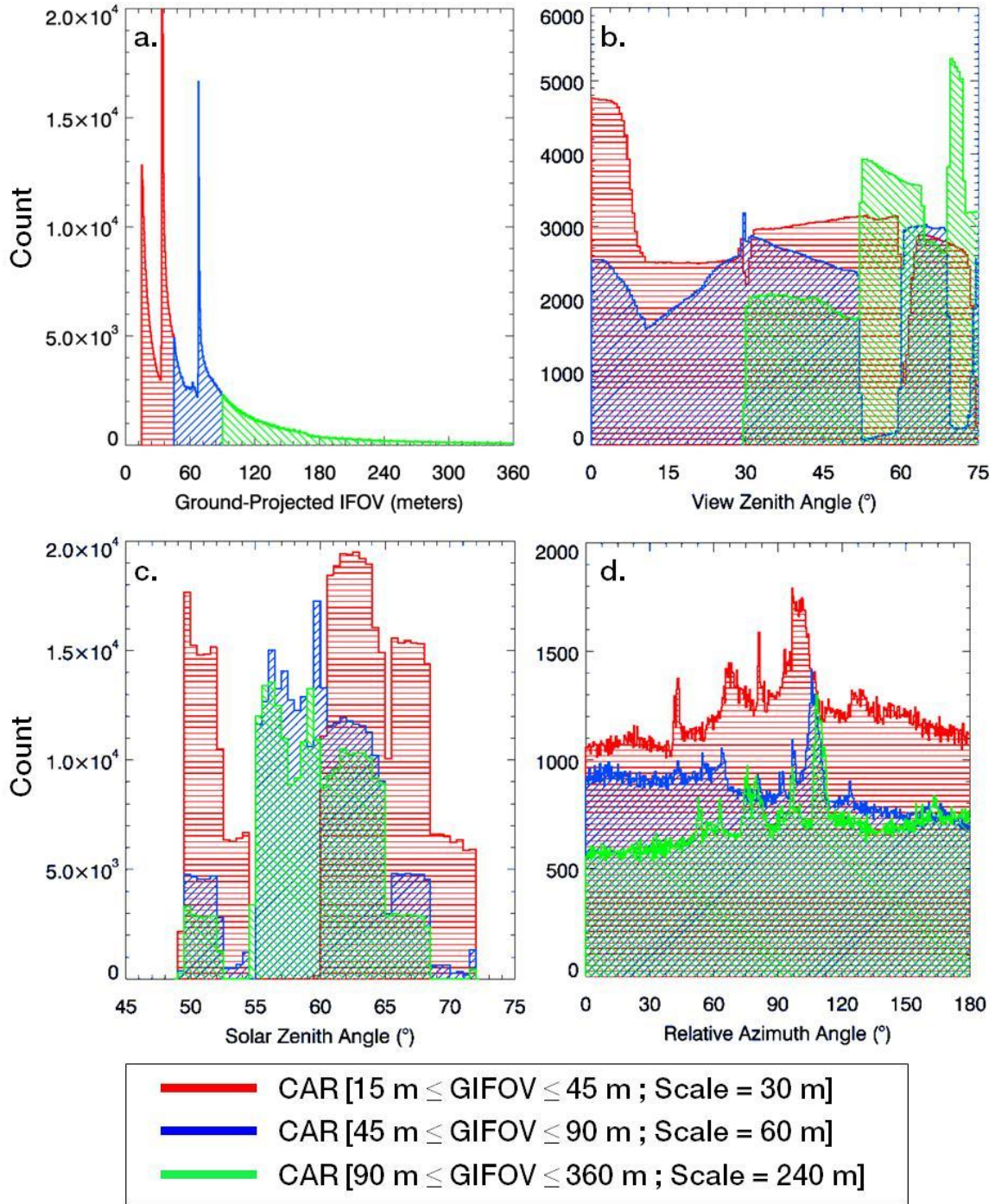


Fig. 7. Distribution of Flight #1928 measurements for three different grids sizes equal to 30 m² (in red), 60 m² (in blue), and 240 m² (in green). (a.) Each grid consists of BRF data from Flight #1928 selected from a distinctive range of GIFOVs. Measurements are also shown as a function of: (b.) view zenith angle; (c.) solar zenith angle; and (d.) relative azimuth angle.

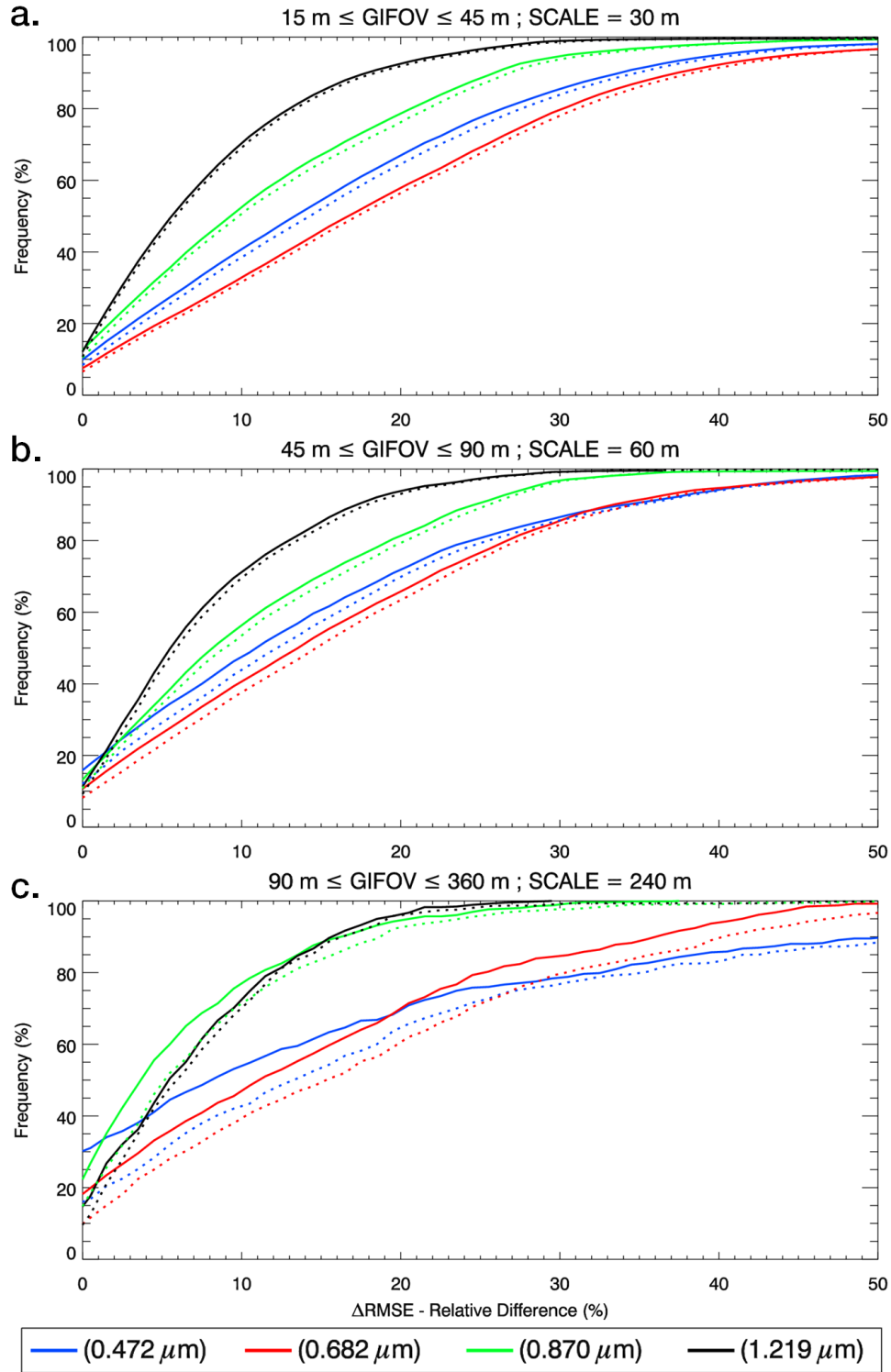


Fig. 8. Cumulative distribution of relative RMSE differences(%) in CAR-derived RossThick-LiSparseReciprocal BRDF model inversions for three grid cell sizes equal to 30 m (a.), 60 m (b.), and 240 m (c.); and for four discrete wavelengths from 0.472 μm to 1.219 μm . Each plot illustrates the robustness of Flight #1928 BRDF retrievals employing a priori archetypal BRDF shapes to describe the surface anisotropy as either: (1) a linear-mixture of different ecosystem types (solid lines); or (2) a single (or dominant) ecosystem type (dotted lines).

Table 2. Cumulative distribution of relative RMSE differences (%) in CAR-derived RossThick-LiSparseReciprocal BRDF model inversions (as illustrated in Fig. 8) for three grid cell sizes equal to (a.) 30 m, (b.) 60 m, and (c.) 240 m, using four discrete wavelengths from 0.472 μm to 1.219 μm , and five frequency limits for ΔRMSE values $\leq 10\%$ to $\leq 50\%$. Numbers before and after each slash are for a priori archetypal BRDF retrievals employing the “linear-mixture” and “dominant” assumptions, respectively.

A. CAR BRDF [$15 \text{ m} \leq \text{GIFOV} \leq 45 \text{ m}$; Scale = 30 m] – % Frequency					
Wavelength	$\Delta\text{RMSE} \leq 10\%$	$\Delta\text{RMSE} \leq 20\%$	$\Delta\text{RMSE} \leq 30\%$	$\Delta\text{RMSE} \leq 40\%$	$\Delta\text{RMSE} \leq 50\%$
$\Lambda = 0.472\mu\text{m}$	42.17% / 39.82%	68.13% / 65.68%	86.19% / 84.67%	95.33% / 94.66%	98.12% / 98.13%
$\Lambda = 0.682\mu\text{m}$	34.17% / 32.85%	59.05% / 57.60%	80.53% / 79.00%	92.70% / 91.84%	96.72% / 96.77%
$\Lambda = 0.870\mu\text{m}$	54.26% / 52.40%	79.72% / 77.43%	95.04% / 94.19%	98.27% / 98.22%	99.38% / 99.60%
$\Lambda = 1.219\mu\text{m}$	72.27% / 71.09%	93.11% / 92.46%	99.00% / 98.73%	99.53% / 99.64%	99.56% / 99.85%
B. CAR BRDF [$45 \text{ m} \leq \text{GIFOV} \leq 90 \text{ m}$; Scale = 60 m] – % Frequency					
Wavelength	$\Delta\text{RMSE} \leq 10\%$	$\Delta\text{RMSE} \leq 20\%$	$\Delta\text{RMSE} \leq 30\%$	$\Delta\text{RMSE} \leq 40\%$	$\Delta\text{RMSE} \leq 50\%$
$\Lambda = 0.472\mu\text{m}$	48.77% / 45.25%	72.89% / 71.00%	87.13% / 86.14%	94.62% / 94.30%	98.40% / 98.45%
$\Lambda = 0.682\mu\text{m}$	41.93% / 38.94%	66.90% / 64.53%	84.88% / 80.13%	94.29% / 90.31%	97.89% / 97.78%
$\Lambda = 0.870\mu\text{m}$	58.00% / 55.24%	82.27% / 80.36%	97.10% / 96.88%	99.36% / 99.52%	99.47% / 99.81%
$\Lambda = 1.219\mu\text{m}$	72.83% / 71.35%	94.33% / 93.69%	99.26% / 99.22%	99.53% / 99.79%	99.53% / 99.84%
C. CAR BRDF [$90 \text{ m} \leq \text{GIFOV} \leq 360 \text{ m}$; Scale = 240 m] – % Frequency					
Wavelength	$\Delta\text{RMSE} \leq 10\%$	$\Delta\text{RMSE} \leq 20\%$	$\Delta\text{RMSE} \leq 30\%$	$\Delta\text{RMSE} \leq 40\%$	$\Delta\text{RMSE} \leq 50\%$
$\Lambda = 0.472\mu\text{m}$	54.82% / 43.41%	70.88% / 65.68%	78.80% / 77.27%	85.87% / 83.64%	89.94% / 88.64%
$\Lambda = 0.682\mu\text{m}$	48.46% / 40.71%	71.45% / 62.04%	86.37% / 85.14%	94.86% / 94.72%	99.23% / 96.93%
$\Lambda = 0.870\mu\text{m}$	78.42% / 72.79%	94.96% / 93.03%	99.28% / 97.62%	100.00% / 99.15%	100.00% / 99.83%
$\Lambda = 1.219\mu\text{m}$	74.80% / 72.17%	96.71% / 96.28%	100.00% / 99.35%	100.00% / 99.35%	100.00% / 99.87%

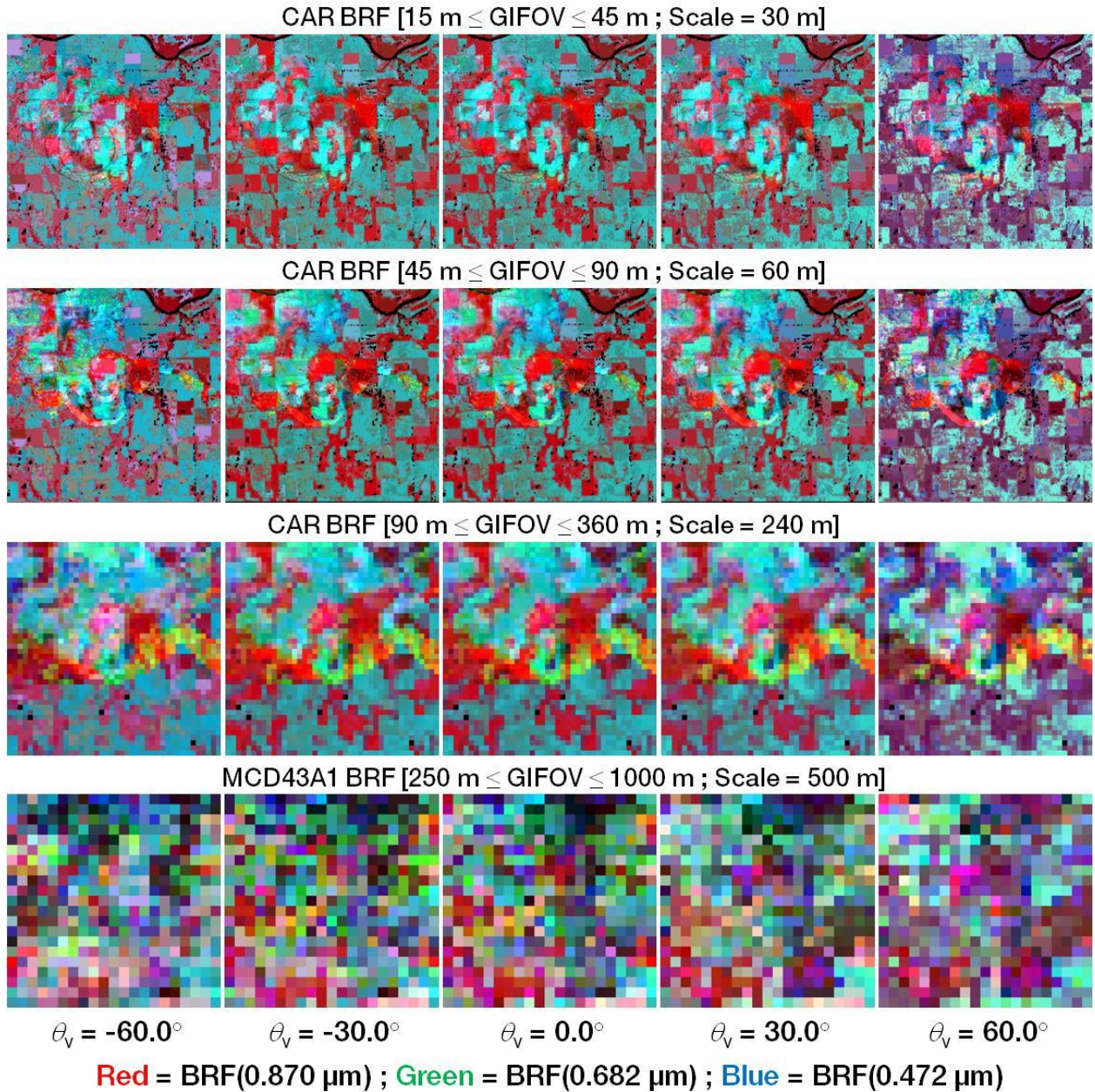


Fig. 9. Principal plane surface BRF fields derived from CAR Flight #1928 and MODIS Collection 5 (MDC43A1) BRDF model parameters over the CART site.

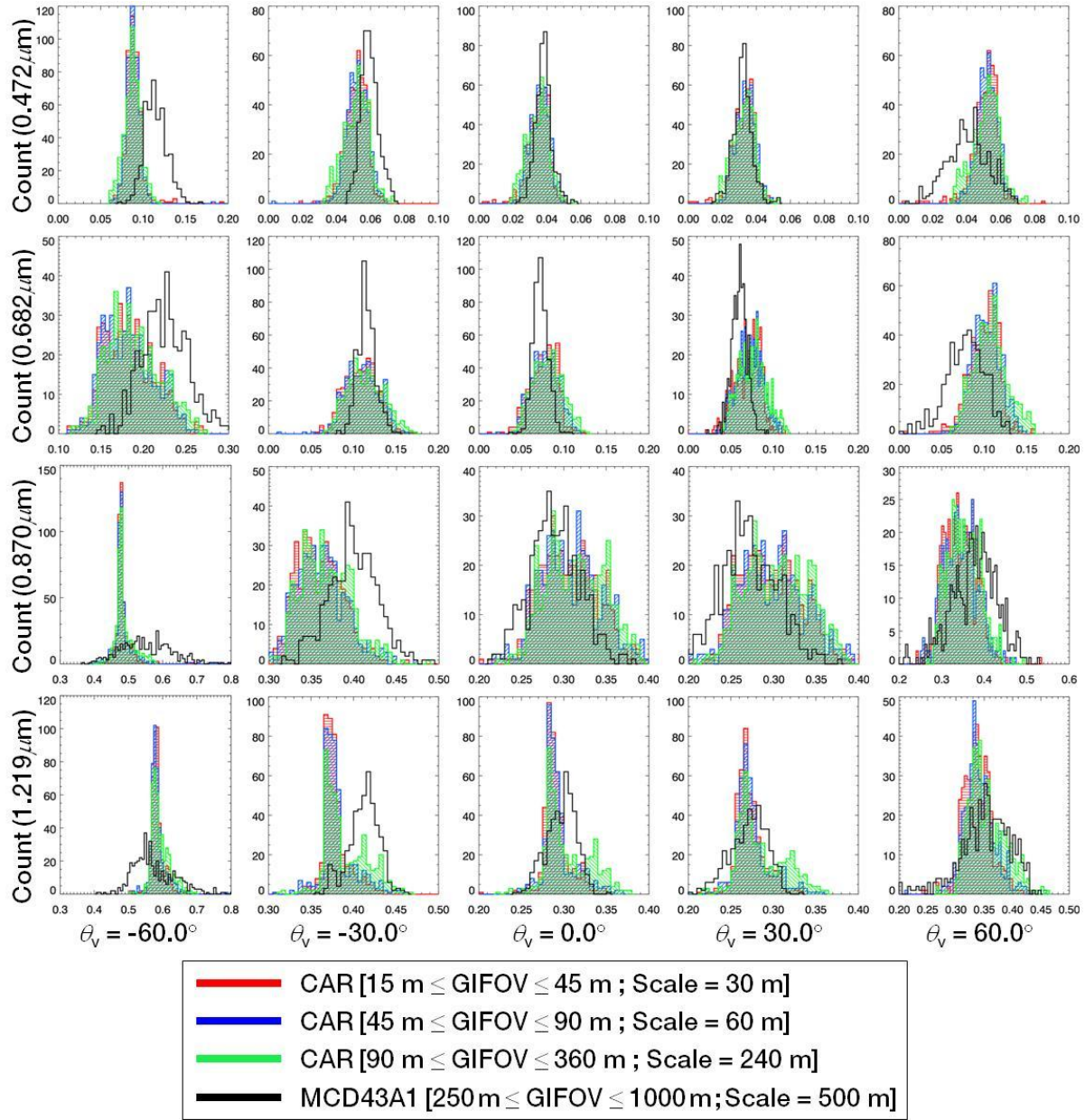


Fig. 10. Distribution of spatially distributed BRF retrievals from CAR and MCD43A1 BRDF model inversions for four discrete wavelengths from 0.472 μ m (top) to 1.219 μ m (bottom).

Table 3. Accuracy^a, precision^b, and uncertainty^c (APU) values resulting from comparisons between CAR-derived surface BRFs and MCD43A1 for each of the spatially-distributed BRDF fields examined in Fig. 10.

Band	VZA	CAR [15 m ≤ GIFOV ≤ 45 m; Scale = 30 m] vs. MCD43A1			CAR [45 m ≤ GIFOV ≤ 90 m; Scale = 60 m] vs. MCD43A1			CAR [90 m ≤ GIFOV ≤ 360 m; Scale = 240 m] vs. MCD43A1		
		Accuracy	Precision	Uncertainty	Accuracy	Precision	Uncertainty	Accuracy	Precision	Uncertainty
0.472μm	-60°	-32.70%	20.99%	0.0313	-30.20%	20.49%	0.0380	-29.63%	19.83%	0.0311
0.472μm	-30°	-17.71%	20.55%	0.1150	-17.47%	21.76%	0.0120	-16.74%	19.85%	0.1120
0.472μm	0°	-11.18%	39.02%	0.0097	-5.96%	36.40%	0.0172	-13.38%	26.18%	0.0082
0.472μm	30°	-7.95%	28.49%	0.0107	4.41%	28.19%	0.0217	-2.06%	28.02%	0.0081
0.472μm	60°	17.68%	28.11%	0.0194	22.91%	29.80%	0.0314	18.92%	27.94%	0.0178
0.682μm	-60°	-25.40%	24.93%	0.0580	-24.68%	24.92%	0.0591	-22.12%	23.25%	0.0526
0.682μm	-30°	-9.14%	22.58%	0.0223	-9.48%	22.40%	0.0224	-3.91%	20.57%	0.0219
0.682μm	0°	1.18%	34.31%	0.0184	3.96%	30.78%	0.0231	6.33%	23.29%	0.0205
0.682μm	30°	16.66%	25.52%	0.0209	15.86%	27.63%	0.0280	16.13%	23.47%	0.0241
0.682μm	60°	17.94%	47.66%	0.0372	26.97%	42.11%	0.0450	25.47%	26.51%	0.0426
0.870μm	-60°	-33.51%	12.10%	0.1717	-33.62%	12.13%	0.1697	-32.68%	13.02%	0.1673
0.870μm	-30°	-11.50%	11.61%	0.0567	-11.75%	12.86%	0.0582	-9.46%	12.30%	0.0541
0.870μm	0°	4.26%	14.34%	0.0477	2.92%	24.84%	0.0536	6.60%	14.55%	0.0530
0.870μm	30°	6.90%	16.80%	0.0554	11.40%	14.48%	0.0626	9.65%	16.11%	0.0611
0.870μm	60°	11.63%	21.79%	0.0748	11.51%	21.47%	0.0831	7.72%	19.52%	0.0705
1.219μm	-60°	-17.70%	8.58%	0.1141	-17.36%	8.96%	0.1133	-16.31%	8.86%	0.1080
1.219μm	-30°	-9.12%	6.76%	0.0423	-8.90%	8.19%	0.0434	-6.13%	8.86%	0.0403
1.219μm	0°	-2.51%	8.35%	0.0252	-4.76%	43.59%	0.0346	1.28%	11.16%	0.0352
1.219μm	30°	4.08%	13.09%	0.0415	7.78%	15.52%	0.0412	0.13%	10.66%	0.0289
1.219μm	60°	4.68%	16.31%	0.0605	0.53%	17.07%	0.0655	0.25%	17.03%	0.0551

^a Accuracy = arithmetic mean(CAR – MODIS) × arithmetic mean(CAR)⁻¹ × 100 %

^b Precision = standard deviation(CAR – MODIS) × arithmetic mean(CAR)⁻¹ × 100 %

^c Uncertainty: Absolute RMSE = $\sqrt{\text{arithmetic mean}(\text{CAR} - \text{MODIS})^2}$